Evaluating EU-Region Level Innovation Readiness: A Longitudinal analysis using Principal Component Analysis and a Constellation Graph Index Approach

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Abstract

Innovation is a component of economic development, with emphasis on entrepreneurship and small business activity. This longitudinal study evaluates innovation readiness drivers across European regions. The following research questions are posed: What are the sets of innovation drivers in Europe? What is their relative importance? How do they differ between regions over time? The study uses principal component analysis (PCA) and the constellation graph index approach. Three principal component drivers of innovation are identified: innovation system, absorptive capacity, and IP protection. The aggregation of component details reveals an innovation readiness dimension for each European region in a specific year. Variations in results for different years are discussed. The study covers many countries. Innovation readiness across regions is examined. The results show that constituent innovation driver variables contribute to performance over time. Different patterns are revealed for high and low innovation regions. The relationships between innovation drivers are evaluated.

1. Introduction

Creating the right conditions for successful, sustained innovation requires the long-term development of multiple activities by numerous stakeholders (Albats et al., 2020). In other words, it requires a systematic approach. While innovation is considered increasingly important in economic, social, and environmental solutions (Beynon et al., 2016b) in Europe (Tamayo-Orbegozo et al., 2017), many European regions struggle to develop the regional innovation systems needed to generate high innovation levels (Beynon et al., 2021). There is a need to study the importance and impact of innovation factors because a wide range of variables are potentially important in driving innovation to help European regions develop successfully (Nieto and Santamaria, 2010).

Entrepreneurship is also regarded as central to this type of economic development in Europe. Small and medium-sized enterprises (SMEs) are crucial in driving successful innovation creation, dissemination, and use (McCann & Ortega-Argilés, 2016; Hervás-Oliver et al., 2021a, b). Within the European Union (EU), a core component of government policy at the regional level is, unsurprisingly, the regional innovation system (Caloffi et al., 2015). Firms' absorptive capacity is also regarded as important to allow exploration and exploitation of external knowledge (Radicic et al., 2019) generated by the innovation system. Mendonca et al. (2004) have argued that intellectual property (IP) related to processes such as trademarks, which also includes design, plays a crucial role in the process of marketing innovation. Such IP processes are key explicit indicators, differentiating goods and services in the marketplace and protecting advantages. Thus, IP can assist both the success of the innovations themselves and the sector shifts they cause in the wider economy. Additionally, the relevance of the concepts of regional innovation ecosystems (Schaeffer & Matt, 2016) and entrepreneurial ecosystems (Dedehayir et al., 2018) means that government policy should link innovation and activities that support entrepreneurship to produce positive regional economic outcomes (Galbraith et al., 2017). There is a need to study the importance and impact of innovation factors because a wide range of variables are potentially important in driving innovation to help European regions develop more successfully (Nieto & Santamaria, 2010).

The purpose of this article is to investigate the importance of this wide range of potentially interrelated innovation variables over time. The specific research questions addressed by this study are as follows: What are the sets of innovation-related drivers in Europe? How important is each one? How do they differ across different regions over time? To investigate these questions, a nascent two-stage analysis approach is used. This two-stage analysis follows the indications of Beynon et al. (2016a). First, principal component analysis

(PCA) is applied to the entrepreneurship and innovation driver variables. Next, the constellation graph index approach is applied to the PCA findings. The PCA groups the entrepreneurship and innovation drivers into a smaller number of uncorrelated principal components. These components are named to describe their constituent driver variables. (i) The *innovation system* component captures the way in which knowledge can be drawn to it and moved within it. (ii) The absorptive capacity component refers to the ability to use knowledge generated both within and outside the organization. (iii) The IP protection component refers to the ability to create, use, and protect innovation in the marketplace. The constellation graph index approach then highlights each variable's contribution to these components. It also reveals how the components can be aggregated to give a final innovation readiness index. This information is shown on the consistent constellation graph domain, which also shows index values over a consistent domain running from 0 to 1.

PCA and the constellation graph index approach have been combined in several research areas, including education (Fuller et al., 2019) and information and communication technology (ICT) awareness (Galazka et al., 2018). With data on every two years from 2011 to 2019, this study follows the approach of Beynon *et al*. (2019) by providing longitudinal analysis. Following the indications of Beynon et al. (2016a) and Fuller et al. (2019), in innovation terms, the analysis extends the findings of the PCA using the constellation graph method of data representation. The initial graphical and numerical findings are discussed in terms of components, their interrelationships, and final innovation readiness scores. Variations in results across years are also illustrated. To date, longitudinal research in this area is lacking. With a view to possible use in policymaking, country-level analysis is performed, based on the regions within each country.

The rest of the paper follows a clear structure. Section 2 discusses the drivers of innovation in Europe, including at the regional level. Section 3 describes the methods and introduces the European regional innovation data. The results of the initial PCA are also presented, and the innovation-related components are outlined. Section 4 presents the results of the constellation graph index approach analysis, with emphasis on graph- and index-based findings. Section 5 then discusses the longitudinal perspective of the results. Examples from a small number of European regions are provided. Section 6 offers conclusions as well as directions for future research.

2. Theoretical framework: Innovation and European regions

This study is based on the theoretical framework of Hervás-Oliver *et al.* (2021b). Accordingly, the study uses place-based regional innovation systems and the SME innovation literature (including SME capabilities as used by Hervás-Oliver et al., 2021a) as the key frameworks for the analysis. This approach is also aligned with the regional absorptive capacity concept used by Beynon et al. (2021). In Europe, a region's research capacity is vital in subsequent firm innovation (Sternberg & Arndt, 2001). Increasing the volume and value of entrepreneurial activity that drives innovation is a critical policy challenge (Landabaso, 2014). Unsurprisingly, therefore, a range of regional innovation policies that support networking among heterogeneous organizations have been introduced in Europe. These policies are inspired by concepts such as smart specialization and regional innovation systems (Caloffi et al., 2015).

At the system level, research and development (R&D) intensity in both the private and public sectors is an important part of this debate. The empirical research on the EU typically focuses on private sector R&D and subsidization. Studies of the effect of public support on measures of innovation and firm performance other than private R&D expenditure are relatively scarce (Radicic et al., 2016). In contrast, Matei and Aldea (2012) used public sector R&D to rank national innovation systems according to their technical efficiency. They were selected to describe the quality of public sector intellectual assets. Non-R&D based innovation can also take place. Heidenreich (2009) used non-R&D innovation expenditure as an important part of a study of innovation patterns and the location of low- and medium-technology industries in Europe. This brief review of the literature illustrates the heterogeneous knowledge bases that may be necessary for an effective innovation system and thus the need to take alternate types of knowledge bases into account.

Květoň and Kadlec (2018) cited three interlinked knowledge bases as important to a region's innovation capacity. "Codified analytical knowledge" (including publications) can be combined with "synthetic knowledge" (existing knowledge with internal firm learning) and "symbolic tacit knowledge" (consistent with local cooperation). Such combinations determine innovation outcomes for firms and regions. Human capital is an important conduit for different types of knowledge. Codified analytical knowledge is seen as related to public-private collaboration, synthetic knowledge is seen as related to internal firm innovation, and symbolic tacit knowledge is seen as related to innovation collaboration in the value chain.

Lau and Lo (2015) reported on innovation that occurs via a regional innovation systems (RIS) approach. Such innovation is supported by policies such as education and training, knowledge-intensive support services, and value chains that assist firms with their internal absorptive capacity. Research has also been conducted on the elements that support innovation activities in general and collaborative (RIS-compatible) approaches specifically. De Nonni et al. (2018) identified measures of tertiary education as a proxy for more general human capital to study collaborations. They observed that regional innovation performance partly depends on human capital within the local economy.

Rodríguez-Pose and Crescenzi (2008) used an indication of accumulated skills at the local level as part of a region’s “social filter”. They found that lifelong learning is positively associated with regional growth, particularly where R&D investment and knowledge spillovers are also present. This finding was observed because human capital within the local economy affects the ability of a region to create and absorb knowledge, specifically in relation to universities. This process is difficult for SMEs (Caloffi et al., 2015). SMEs with absorptive capacity via higher education and internal innovation are more likely to improve performance (Hu & Hughes, 2020).

Unsurprisingly, therefore, universities are important direct contributors to innovation in the European regional ecosystem (Pugh et al., 2019). Szopik-Depczyńska et al. (2020) also reported that well-cited research emanating from a region’s universities offers a measure of the quality and attractiveness of the regional research system in the EU context. European SMEs seeking cooperation with higher education institutions (HEIs) or public-sector knowledge actors, can then follow a low commercial or market risk strategy (Radicic et al., 2019) by simply using already published research (Corral de Zubielqui et al., 2015). Co-publication thus offers a measure of greater interactivity between these regional actors (Autant-Bernard et al., 2006). More broadly, Matei and Aldea (2012) studied national innovation systems’ technical efficiency, observing that co-publications where at least one co-author was international offered a further indicator of the quality of the research system.

However, collaboration within the industry is often seen as more important than between universities and industry. For instance, according to Huggins and Thompson (2015) and De Noni et al. (2018), collaborative networks of local businesses are important for innovation. Corral de Zubielqui et al. (2015) showed that SME knowledge acquisition from customers and suppliers is more likely to occur than acquisition from government or HEIs. In addition, Sternberg and Arndt (2001) argued that individual firm and regional capacities are linked, noting that in Europe, firm-specific innovation factors have a stronger effect than region-specific factors or other external potential drivers.

However, Beynon et al. (2021) highlighted the research gap in relation to studies investigating what Gray (2006) identified as “absorptive capacity” in terms of both crosssectional and time-series analyses in Europe. The theory surrounding absorptive capacity predicts that external knowledge is more easily absorbed where there are also strong existing knowledge stocks and capacity (Miguélez & Moreno, 2015). This idea is potentially important in the regional innovation debate. Radicic et al. (2019) showed that, along with capabilities, a firm's internal innovation capacity, which is consistent with the concept of absorptive capacity (Hervás-Oliver et al., 2021a), is necessary to enable the exploration and exploitation of external knowledge from networking and collaboration activities (Huang & Rice, 2009).

Gray (2006) also identified absorptive capacity as a key component in this debate. Absorptive capacity is defined as including a firm's overall capacity for learning, internally implementing and disseminating new knowledge, and using new resources and technologies. Radicic *et al*. (2019) found that a firm's technological product and process innovations, non-technological (organizational and marketing) innovations, and the subsequent success of product and process innovations in the market (innovative sales) are potentially complementary. Szabo and Herman (2012) found that product, process, and marketing innovations introduced by SMEs in the EU were both part of the broader innovation system and were positively related to economic development in the EU.

Szopik-Depczyńska et al. (2020) cited various measures of IP as measures of the level of intellectual assets in the regional innovation system. While the primary IP measure is usually patents (Burrus et al., 2018; Carayannis & Provance, 2008), Mendonca et al. (2014) explained that the use of trademarks by firms in a region is also a good indicator of broader innovation and industrial change. This indicator is effective because it signals an exploitation focus of firms, which seek to protect the competitive advantages generated by their brand. Candelin-Palmqvist et al. (2004) reviewed the literature, finding support for the role of IP in innovation in general. They also specifically identified the positive relationship between industrial design and firm performance outcomes. Likewise, Matei and Aldea (2012) cited trademarks as being of specific relevance in ranking national innovation systems according to technical efficiency.

Temporal changes are also important to understand the dynamic processes that help regions develop innovation systems over time. Borrás and Jordana (2016) validated this idea for the Basque region. Sanz-Menéndez and Cruz-Castro (2005) also reported that the innovation promotion policies of regional governments often follow a dichotomy of either the "the academic approach", focused on universities and public research centers, and the "business approach", focused on technology hubs and innovative firms. This finding also supports the need to explore the most successful policy mixes in improving the innovation system and its outcomes.

In summary, a range of interlinked region-, firm-, and innovation-(IP)-related factors are potentially important in determining the innovation capacity of a region. Examining their relative importance and their patterns of interaction in different types of regions is also of relevance in this debate.

3. European regional innovation data set

The data for this study came from the EU Regional Innovation Scoreboard (RIS) data set. This data set uses Eurostat and other internationally recognized data. This data set provides comparable regional innovation data for EU member states, regional data for the non-EU countries of Norway, Serbia, and Switzerland, and country-level data for the EU member states of Cyprus, Estonia, Latvia, Luxembourg, and Malta. In these countries, NUTS 1 and NUTS 2 levels are identical to the country level. Therefore, this study used data from the EU RIS for a large sample of European regions and countries, although a small number of European regions were not considered because of missing values for the variables of interest. One feature of this data set is the collection of data on a wide range of innovation variables. Table 3 lists those used in the analysis. This data set offers data for every two years from the period 2011 to 2019. The number of European regions by country is shown in Table 1. The study covered 25 countries. The numbers of associated European regions ranged from two (Croatia, Lithuania and Slovenia) to 38 (Germany). A total of 229 European regions were included.

Table 1. Number of regions by country

AT - Austria - 3	BE - Belgium - 3	BG - Bulgaria - 6	HR - Croatia - 2	CZ - Czech Republic - 8
DK - Denmark - 5	FI - Finland - 4	FR - France - 13	DE – Germany - 38	EL - Greece - 11
HU - Hungary - 8	IE - Ireland - 3	IT - Italy - 21	LT - Lithuania - 2	NL - Netherlands - 12
NO - Norway - 7	PL - Poland - 17	PT - Portugal - 6	RO - Romania - 8	RS - Serbia - 4
SK - Slovakia - 4	SI - Slovenia - 2	ES - Spain - 18	SE - Sweden - 8	UK - United Kingdom - 12

3.1. PCA of European regional innovation data set

In this sub-section, the results of PCA of the European regional innovation data set are presented. The aim of this analysis was to identify a set of uncorrelated principal components from a set of possibly correlated variables (see Hair et al., 2010). Examples of PCA in innovation research include studies of regional technological efficiency (Chen et al., 2010) and organizational factor and innovation (Subramanian et al., 2016). The PCA of the 13 variables included in this study (Table 3) was used to investigate whether there are uncorrelated principal components of the innovation drivers across these European regions. Technical details on the technique of PCA are provided by Hair et al. (2010).

For evidence of the structure of the variables, including correlations, the Kaiser-Meyer-Olkin measure of sampling adequacy (MSA) and Bartlett's test of sphericity (BTS) were conducted. The results for the MSA (0.846) and BTS (approx. Chi-square = 10749.928, sig. = 0.000) suggest that it was acceptable to continue with the PCA. The principal component extraction results are presented in Table 2.

Table 2. Principal component extraction results

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	5.734	44.106	44.106	5.734	44.106	44.106	4.210	32.381	32.381
2	2.085	16.037	60.143	2.085	16.037	60.143	3.142	24.169	56.550
3	1.415	10.886	71.029	1.415	10.886	71.029	1.882	14.479	71.029
4	.847	6.515	77.544						
5	.817	6.286	83.830						
6	.484	3.724	87.554						

Extraction method: principal component analysis.

This analysis adhered to the approach of extracting principal components with eigenvalues above 1.000 so that each component would explain more variance than an individual variable. Three principal components can be extracted from Table 2. These components explain 71.029% of the total variance, above a possible acceptability threshold of 60% (Hair et al., 2010). Table 3 shows the 13 innovation driver variables included in the study based on the PCA. These variables cover a range of innovation drivers (collaboration, education-based, publication-based, and R&D). An explanation of the statistical analysis is provided to improve the understanding of the range of values across different European regions. In contrast to the literature, patents and private sector R&D were not included in the overall index. The reason for excluding these factors was that, during the PCA, they were found to load on more than one principal component. They were therefore removed from the analysis.

Table 3. Definition and descriptive statistics for innovation variables

Variable	Description	[Min, Mean, Max] Standard deviation	Studies where variable has been used in similar contexts
INN_SME_ COLLAB	Index created by comparing innovative SMEs collaborating with others (having co-operation agreements on innovation activities with other firms or institutions) as a percentage of SMEs in each region against the EU average for this indicator.	[0.000, 93.025, 264.072] 57.519	Recent decades have seen a range of regional innovation policies supporting networking among a wide range of organizations, inspired by concepts such as regional innovation systems and smart specialization (Caloffi et al., 2015). De Noni et al. (2018) identified collaborative networks of local firms and other actors as important. Radicic et al. (2019) found that cooperation increases firms' innovativeness and benefits commercial outcomes. Květoň and Kadlec (2018) also used this variable.
LIFELONG_ LEARNING	Index created by comparing the percentage of the population aged 25–64 years participating in lifelong learning in each region against the EU average for this indicator.	[0.000, 96.503, 306.931] 68.868	Lifelong learning is an indication of accumulated skills at the local level, as part of the social filter. Rodríguez-Pose and Crescenzi (2008) found that lifelong learning is positively associated with regional growth. This association is particularly strong in regions where R&D investment and knowledge spillovers are also present.
TERD_EDUC_ 30_34	Index created by comparing the percentage of the population aged 25–34 years in each region having completed tertiary education against the EU average for this indicator.	[0.000, 92.945, 235.002] 46.541	De Noni et al. (2018) showed that regional innovation partly depends on local human capital. They used tertiary educational attainment as a proxy for human capital. Żelazny and Pietrucha (2017) used similar though not identical measures to proxy for human resources as an enabler of innovation.
INT_CO_ PUBLICATIONS	Index created by comparing the number of scientific publications with at least one co-author based abroad in each region as a proportion of the total population in each region against the EU average for this indicator.	[0.000, 101.812, 239.490] 52.371	Matei and Aldea (2012) used this variable in their study ranking national innovation systems according to technical efficiency to describe the quality of the research system.
PUB_PRIV_CO_ PUBLICATIONS	Index created by comparing public-private (excludes the private medical and health sector) co-publications (academic publications) per million inhabitants in each region (publications assigned to the country/countries where the businesses or other private sector organizations are located) against the EU average for this indicator.	[0.000, 82.698, 256.591] 54.682	Matei and Aldea (2012) used this variable in their study ranking national innovation systems according to technical efficiency to describe the quality of research collaboration among firms and the public sector. Radicic et al. (2019) identified this type of cooperation as relatively low risk. Autant-Bernard et al. (2006) used co-publications as a regional interactivity measure in their study of the creation of biotech companies in France. Żelazny and Pietrucha (2017) used the same measure as a proxy for linkages and entrepreneurship as enablers of innovation.
MOST_CITED_ PUBLICATIONS	Index created by comparing the number of scientific publications among the top 10% most cited publications worldwide for each region as a proportion of the total population in each region against the EU average for this indicator.	[0.000, 84.087, 195.453] 34.268	Szopik-Depczyńska et al. (2020) used this variable in their assessment of innovation level and local development of EU regions to measure the quality and attractiveness of the regional research system.
PUB_RD	Index created by comparing all R&D expenditure in the government and higher education sectors as a percentage of GDP in each region against the EU average for this indicator.	[0.267, 88.169, 179.608] 37.822	Matei and Aldea (2012) used this variable in their study ranking national innovation systems according to technical efficiency to describe the quality of public sector intellectual assets.
SME_INHOUSE	Index created by comparing SMEs innovating in-house as a percentage of SMEs in each region against the EU average for this indicator.	[0.000, 93.271, 207.597] 40.853	Radicic et al. (2019) showed that internal innovation capacity, which is consistent with absorptive capacity, is also necessary to facilitate external knowledge exploration and exploitation. This variable was also used by Květoň and Kadlec (2018).
PROD_PROCES _INN	Index created by comparing the number of SMEs introducing a new product or process to market as a proportion of total SMEs in each region against the EU average for this indicator.	[0.000, 94.216, 198.630] 40.739	Szabo and Herman (2012) used this variable in their study of the impact of innovative entrepreneurship on economic development in the EU.
MARK_ORG_ INN	Index created by comparing the number of SMEs introducing a new marketing and/or organizational innovation to market as a	[0.000, 91.127, 189.299]	Szabo and Herman (2012) used this variable in their study of the impact of innovative entrepreneurship on economic development in the EU.

	proportion of total SMEs in each region against the EU average for this indicator.	37.424	
NON_RD	Index created by comparing the total innovation expenditure for SMEs (as a percentage of total turnover, excluding intramural and extramural R&D expenditure) in each region against the EU average for this indicator.	[0.000, 100.047, 198.15] 32.161	Heidenreich (2009) used non-R&D innovation expenditure in a study of the innovation patterns and location of low- and medium-technology industries in Europe.
DESIGNS	Index created by comparing the number of designs at the EUIPO as a proportion of GDP (purchasing power standard) in each region against the EU average for this indicator.	[0.000, 76.740, 197.290] 44.023	Szopik-Depczyńska et al. (2020) used this variable in their assessment of innovation level and local development of EU regions to measure the level of intellectual assets in the regional innovation system.
TRADEMARKS	Index created by comparing the number of trademark applications at the EUIPO as a proportion of GDP (purchasing power standard) in each region against the EU average for this indicator.	[1.365, 85.342, 275.963] 55.082	Matei and Aldea (2012) used this variable in their study ranking national innovation systems according to technical efficiency. Szopik-Depczyńska et al. (2020) used this variable in their assessment of innovation level and local development of EU regions to measure the level of intellectual assets in the regional innovation system.

Note: Descriptions derived from Hollanders *et al*. (2019).

In terms of the variables that represent the innovation system, De Noni et al. (2018) identified collaborative networks of local firms and other actors as important. Radicic *et al*. (2019) found that cooperation increases firms' innovativeness and benefits commercial outcomes. The INN_SME_COLLAB variable has been used by Květoň and Kadlec (2018). For education-based variables, De Nonni *et al*. (2018), found that regional innovation partly depends on local human capital. They used tertiary educational attainment as a proxy for broader human capital. Żelazny and Pietrucha (2017) used similar though not identical measures as a proxy for human resources as an enabler of innovation.

The publications-based variables were used to proxy scientific research quality and collaboration. Radicic *et al*. (2019) identified this type of cooperation as relatively low risk. Autant-Bernard *et al*. (2006) used co-publications as a regional interactivity measure in their study of the creation of biotech companies in France. Żelazny and Pietrucha (2017) used the same measure as a proxy for linkages and entrepreneurship as enablers of innovation. R&D measures were included because R&D represents a direct driver of a knowledge-based economy. Much of the existing research covering the EU has focused on R&D and R&D subsidization (Radicic et al., 2016).

Radicic *et al*. (2019) showed that internal innovation capacity, which is consistent with the concept of absorptive capacity, is necessary to enable the exploration and exploitation of external knowledge. The SME_INHOUSE variable has been used by Květoň and Kadlec (2018). A variety of additional absorptive capacity variables (NON_RD, PROD_PROCES_INN, and MARK_ORG_INN) were included for completeness.

Finally, in terms of IP, Candelin-Palmqvist et al. (2004) reviewed the literature and identified the positive relationship between design and performance as well as IP in innovation in general. Mendonca et al. (2014) identified the use of trademarks by firms in a region as an indicator of broader innovation, using a similar variable to TRADEMARKS in their analysis.

The relative association of the 13 innovation driver variables with the three principal components listed in Table 2 is summarized in Table 4.

Table 4. VARIMAX rotated component analysis

Constituent variable/Component	1	2	3
INT_CO_PUBLICATIONS	**.852**	.150	.190
PUB_PRIV_CO_PUBLICATIONS	**.793**	.253	.270
LIFELONG_LEARNING	**.782**	.088	.082
TERD_EDUC_30_34	**.761**	-.304	.075
PUB_RD	**.717**	.229	.068
INN_SME_COLLAB	**.657**	.407	-.102
MOST_CITED_PUBLICATIONS	**.631**	.413	.208
PROD_PROCES_INN	.276	**.877**	.252
SME_INHOUSE	.295	**.869**	.237
MARK_ORG_INN	.202	**.864**	.178
NON_RD	-.124	**.510**	-.306
DESIGNS	-.005	.157	**.864**
TRADEMARKS	.317	.100	**.843**
Cronbach's alpha	0.875	0.847	0.751

Extraction method: principal component analysis. Rotation method: Varimax with Kaiser normalization.[a]
a. Rotation converged in 5 iterations.

In Table 4, the 13 variables are ordered by their largest loading values (i.e., the degree of correspondence between the variable and the component) for each of the three principal components (see Hair *et al*., 2010). The Cronbach's alpha scores for each principal component are also shown in the table. All were greater than 0.750. Hence, they are all considered acceptable in terms of the internal consistency of the component variables. The loading values show that seven, four, and two variables map onto each of the three principal components, respectively. Based on the data in Table 3, the loadings highlighted in bold can be interpreted. Therefore, PCA helped identify three main factors affecting innovation: innovation system, absorptive capacity, and intellectual property protection.

Component 1 relates to the **innovation system** (Inn-Sys). These variables relate most closely to elements of the regional innovation system and the way in which knowledge can be drawn to it and moved within it. The PCA indicates that variables discussed separately in

Hervás-Oliver et al. (2021b) can be seen as falling under the single broader heading of innovation system. The study by Beynon et al. (2021) focused on innovation system variables, using only one variable that fell under the category of absorptive capacity.

Component 2 relates to the **absorptive capacity** (Abs-Cap) of firms. These variables fit most closely with firm-level absorptive capacity (i.e., the ability to use knowledge generated both within and outside the organization). This analysis builds on the research by Beynon et al. (2021) by broadening the number of variables included in the concept of firm absorptive capacity. It also highlights the interrelations between different categories of firm innovation output and internal activities and resources to generate those outputs.

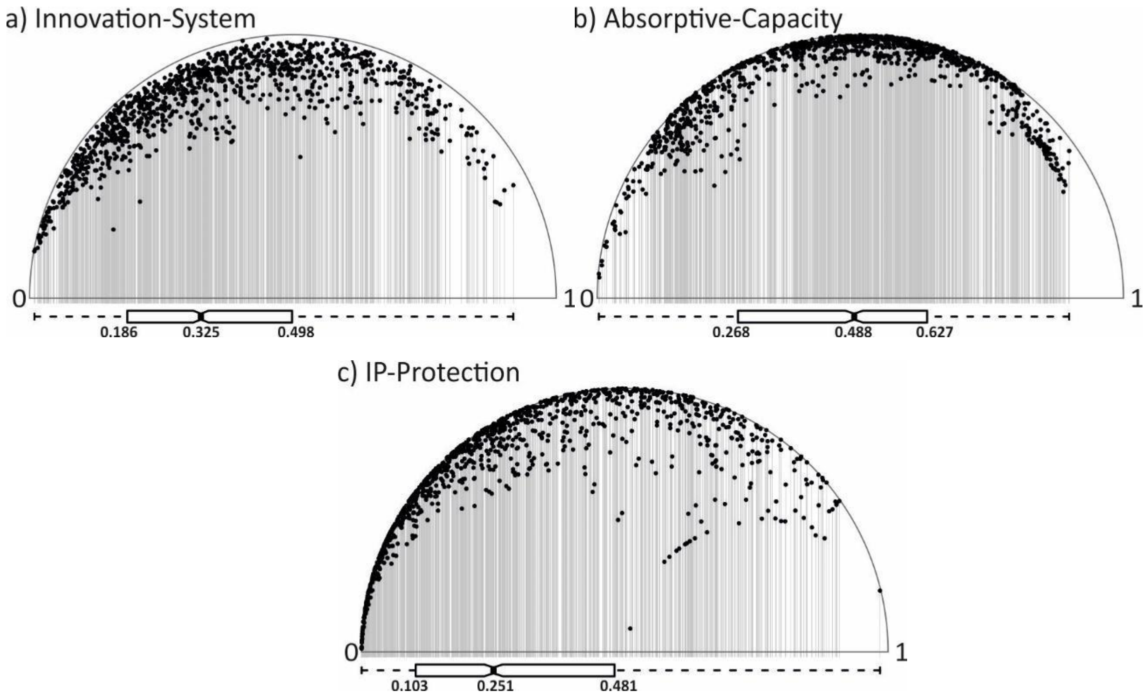
Component 3 relates to **IP protection** (IP-Prot). These variables are explicit IP variables and indicate where there is formal protection of these elements. This component adds an additional dimension to the discussion. Hervás-Oliver et al. (2021b) and Beynon et al. (2021) did not include IP protection in their work.

These components and the loadings and percentage of variance in Tables 4 and 2 are used in the results of the constellation graph index approach presented in the next section.

4. Constellation index graph approach analysis

This section presents the constellation graph index approach analysis of the innovation PCA results. Details of this approach are provided by Beynon *et al*. (2016a). The results are first shown at the principal component level (innovation system, absorptive capacity, and IP protection). Following the constellation graph index approach, normalization, f(x), of each variable value $x_{i,k}$ was performed: $f_k(x_{i,k}) = \frac{(x_{i,k} - \overline{x_{i,k}})}{(\underline{x_{i,k}} - \underline{x_{i,k}})}$ with $\underline{x_{i,k}}$ min and $\underline{x_{i,k}}$ max values given in Table 3. A component complex number z_i (vector) for each European region was found using sets of normalized values and normalized PCA loading values (weights w_k) in the following form: $z_i = \sum_{k=1}^{K} w_k exp\left(\sqrt{-1} f_k(x_{i,k})\pi\right)$. The subsequent component complex number can be represented as a point (constellation coordinate) in a constellation graph. As an example, details of the constellation graph index approach for four European regions are provided in Appendix A. For the extracted principal components (innovation system, absorptive capacity, and IP protection), the sets of component constellation coordinates are shown in the constellation graphs in Figure 1.

Figure 1. Constellation graphs showing innovation system (1a), absorptive capacity (1b), and IP protection (1c) as component coordinates and mapping lines down to corresponding index values

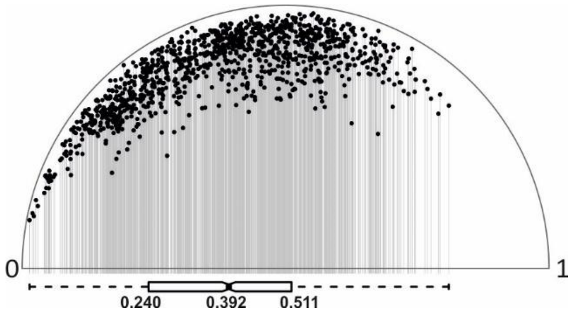


In Figure 1, each constellation graph (upper semi-circle) shows the component-level details of innovation drivers of European regions. These details are shown in terms of constellation coordinates and subsequent index values along the base of the constellation graph (see Appendix A for details of construction). The constellation graph domain from left to right represents low to high component representation. As explained by Beynon *et al*. (2016a), points nearer to the edge of the circle indicate greater consistency in the contributions from the respective constituent innovation driver variables.

The baseline on which the index values are mapped has the consistent domain 0 (left) to 1 (right). Below each constellation graph baseline, boxplots show the distribution of the relevant component index values. By visual inspection of the boxplots, wide boxes imply large spreads of values across each component. In increasing order of median values, the components are ordered as follows: IP protection, innovation system, and absorptive capacity.

For a European region, the three individual component constellation coordinates can be combined. These coordinates are weighted by the normalized percentage of variance component values. This normalization results in aggregated component constellation coordinates and aggregated index values. Appendix A provides details of construction. This aggregated result gives an overall index of innovation readiness (Inn-Rdns) based on the constellation coordinate and index for each European region. The overall innovation readiness results for all European regions are shown in Figure 2.

Figure 2. Constellation graph showing overall innovation readiness constellation coordinate results and mapping lines to subsequent index values



Like Figure 1, Figure 2 shows a constellation graph. This graph illustrates the component aggregation details, termed here as innovation readiness, at the European region level. Each European region is represented by an innovation readiness constellation coordinate and mapped innovation readiness index value. Each value is based on evidence from the respective component details, which themselves are based on innovation variables. A notched boxplot shows the distribution of the resulting innovation readiness index values.

The results so far are for all cases within the European region innovation data set. Longitudinal analysis of the data was also performed using five years of data (2011, 2013, 2015, 2017, and 2019). The results presented by year are based on the index values. They are shown for both the component and overall innovation readiness index values (see Figure 3).

In Figure 3, each graph shows the index values for the different components: 3a) innovation system, 3b) absorptive capacity, 3c) IP protection, and 3d) overall innovation readiness. They are further grouped by year. One-way ANOVA was applied to each of these sets of results. The following statistically significant results were found: innovation system $F(1, 1123) = 7.36$, $p = 0.007$; absorptive capacity $F(1, 1123) = 2.4$, $p = 0.120$; IP protection $F(1, 1123) = 4.49$, $p = 0.034$; innovation readiness $F(1, 1123) = 2.00$, $p = 0.160$. The results show statistically significant differences across years for the innovation system and IP protection principal components. Both had an increasing index value over time. However, the overall innovation readiness index values did not differ across years. The findings are similar at the European regional level, with each region described across the five years of data (see Figure 4).

Figure 3. Component and overall index values by year

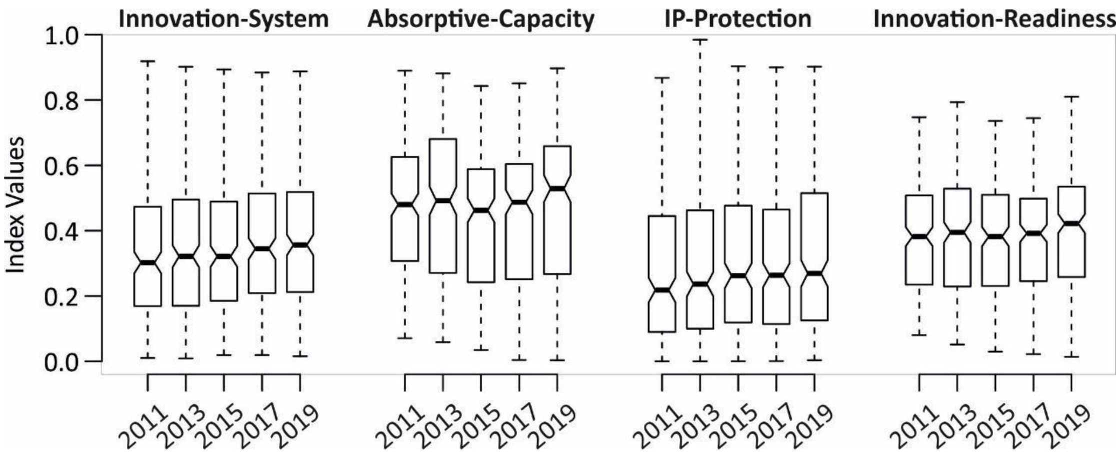
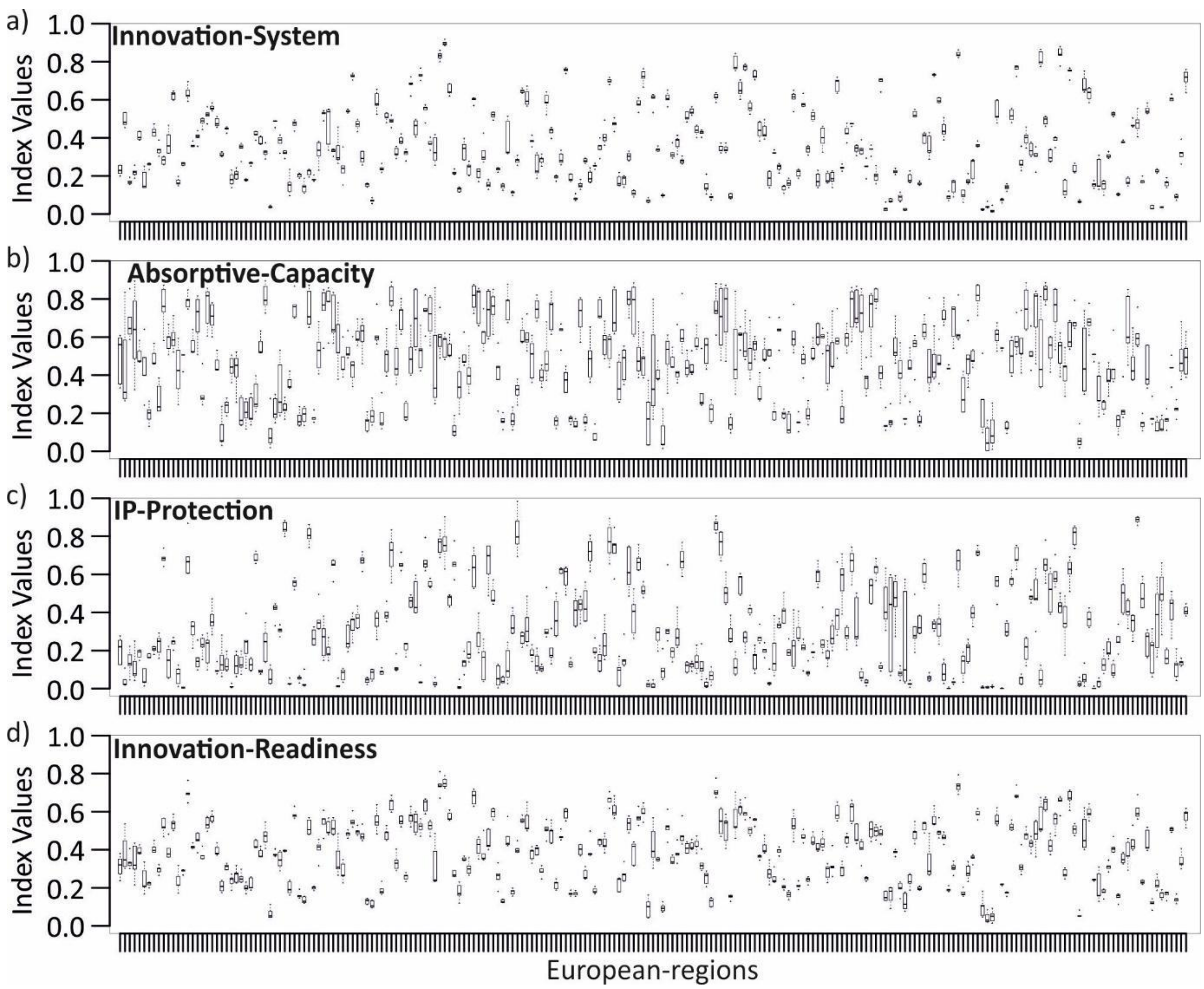


Figure 4. Component index values by European region

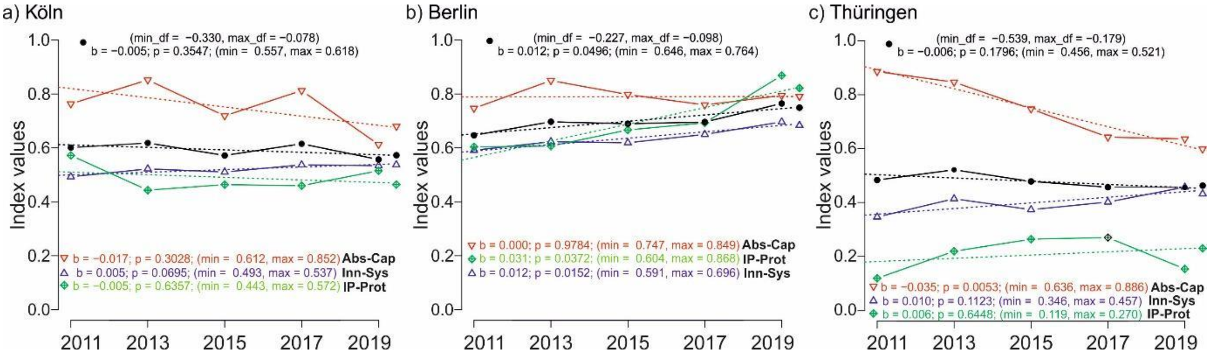


In Figure 4, the component and overall index values are grouped by European region. Each boxplot describes only five year values. The results show variation across European regions. The width of some of the boxplots reflects considerable variation across years for some European regions. One-way ANOVA was applied to each of these sets of results. The following statistically significant results were found: innovation system $F(223, 901) = 200$, $p = 0.000$; absorptive capacity $F(223, 901) = 22.4$, $p = 0.000$; IP protection $F(223, 901) = 51$, $p = 0.000$; innovation readiness $F(223, 901) = 75.7$, $p = 0.000$.

4.1. Combined effect of components on innovation readiness

This section studies the combined effect of these three components on the overall innovation readiness of European regions over time. To illustrate what is meant by overall innovation readiness, the combination plots for three European regions are shown as an example in Figure 5. These plots all correspond to German regions. They show the different possible combinations. Berlin has components that are close together and that generally rise over time. Köln has greater variation in terms of rising and falling components. Thüringen offers an example of considerable disparity between components.

Figure 5. Combination plots for three European regions

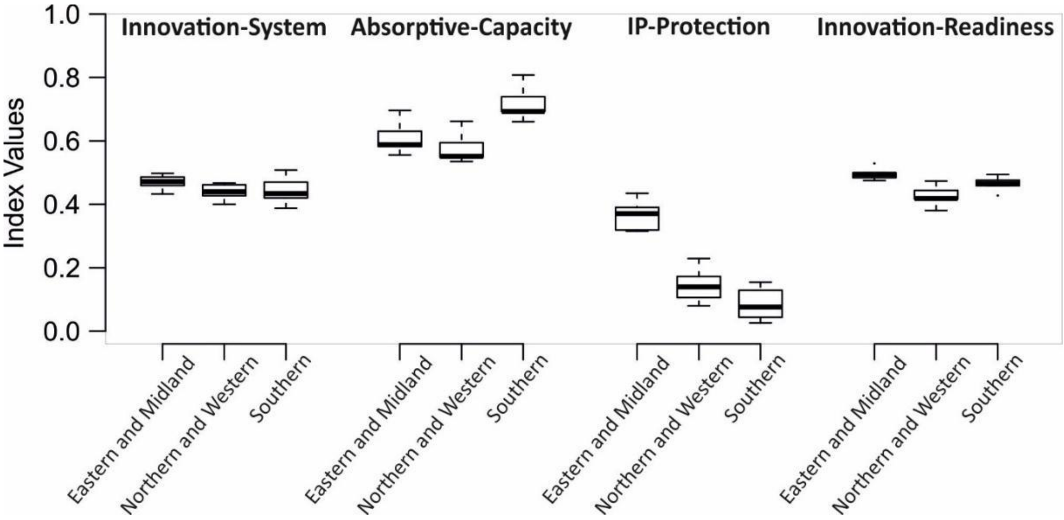


In each combination plot in Figure 5, each of the principal components is reflected by a line of points denoting its index points for every two years between 2011 and 2019. The plots also show statistical details of the associated regression lines of each line plot in the space either above or below the line plots. These details help reveal the trends across different components.

4.2. Country-level analysis

This section studies the index results for sets of European regions for a sample of countries. Three countries are studied: Ireland, the United Kingdom (UK), and France. As indicated in Table 2, these countries have three, 12, and 13, regions, respectively. These three countries were chosen because they are geographically close. Ireland and the UK share a land border. The UK and France are connected by a tunnel and share similarities in production models (specifically the lean model), according to Arundel et al. (2007). These models are correlated with innovation modes. Hence, it was possible to focus on differences in the principal components. For each country, four sets of boxplots and relevant ANOVA statistical results are presented. These results describe the European regions in terms of the principal components of innovation system, absorptive capacity, and IP protection, as well as the overall innovation readiness index (see Figures 6, 7, and 8).

Figure 6. Breakdown of European regions in Ireland (3 regions)



Ireland (Figure 6) has three regions: Eastern and Midland, Northern and Western, and Southern. The results show similar scores for the innovation system component, suggesting a consistent approach across Ireland. For the absorptive capacity component, the Southern region performs best, indicating stronger firm-specific innovation activities in the south of the country. In contrast, the Eastern and Midland region is the most effective for IP protection, perhaps unsurprisingly given that this region includes Dublin. Consequently, the Eastern and Midland and the Southern regions outperform the Northern and Western region in the overall innovation readiness index.

For the United Kingdom (Figure 7), there is much greater variation with regards to the innovation system components. The East of England, London, Scotland, and South East England outperform other UK regions. A similar result is observed (albeit less for Scotland) for the overall index. By comparison, values for the absorptive capacity component seem to be more evenly distributed. London performs worse than many other regions. In contrast, London unsurprisingly performs very strongly with regards to IP protection and overall innovation readiness. South West England seems to have the most consistently high relative performance across all components. Hence, it has an overall innovation readiness score close to that of Scotland, the East of England and South East England. In contrast, Northern Ireland has consistently poor relative performance and thus lags behind the other UK regions in overall innovation readiness. This finding may be at least partly because of geography, with Northern Ireland fitting into neither the UK nor the Irish innovation systems.

Figure 7. Breakdown of European regions in the United Kingdom (12 regions/nations)

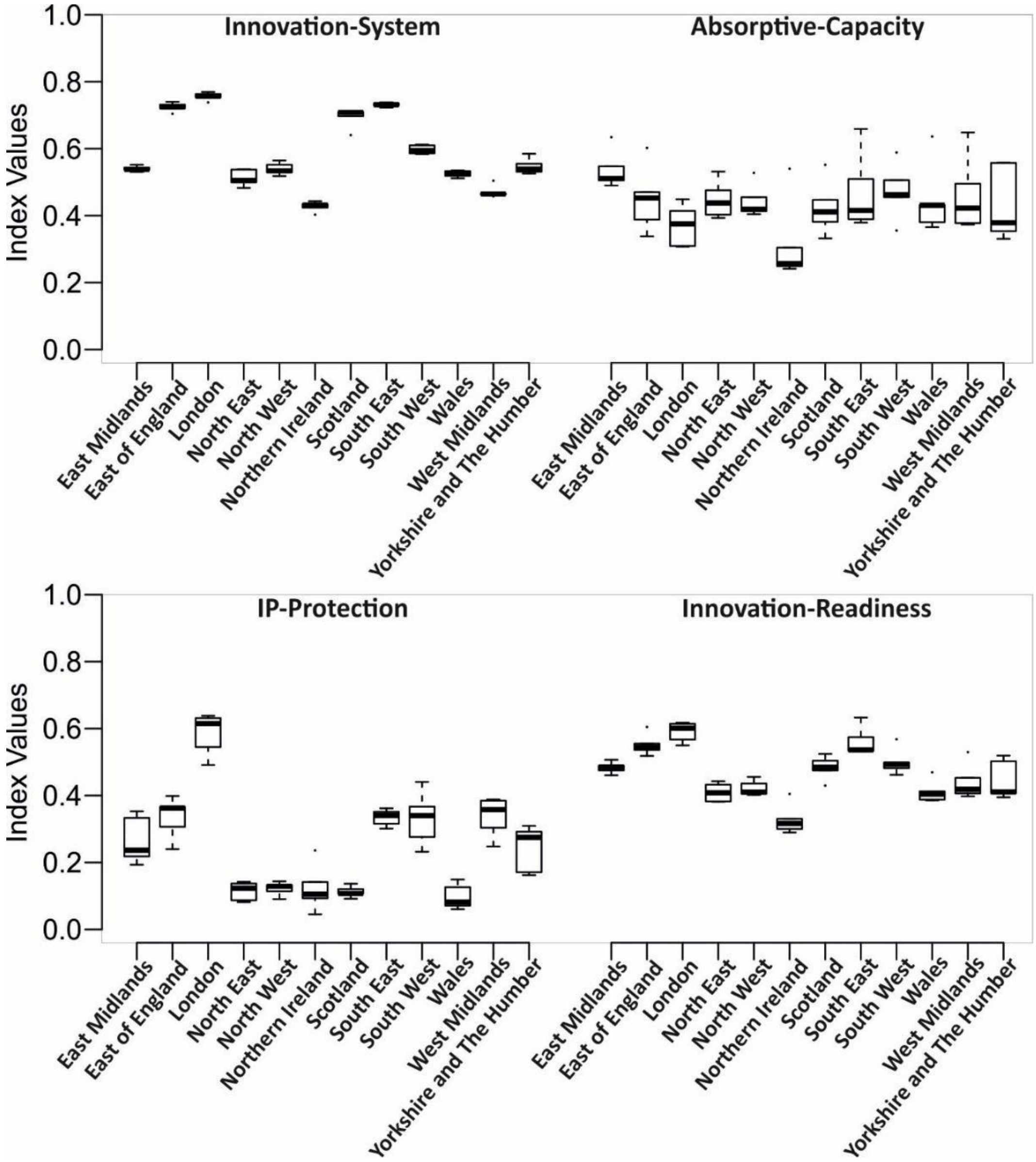
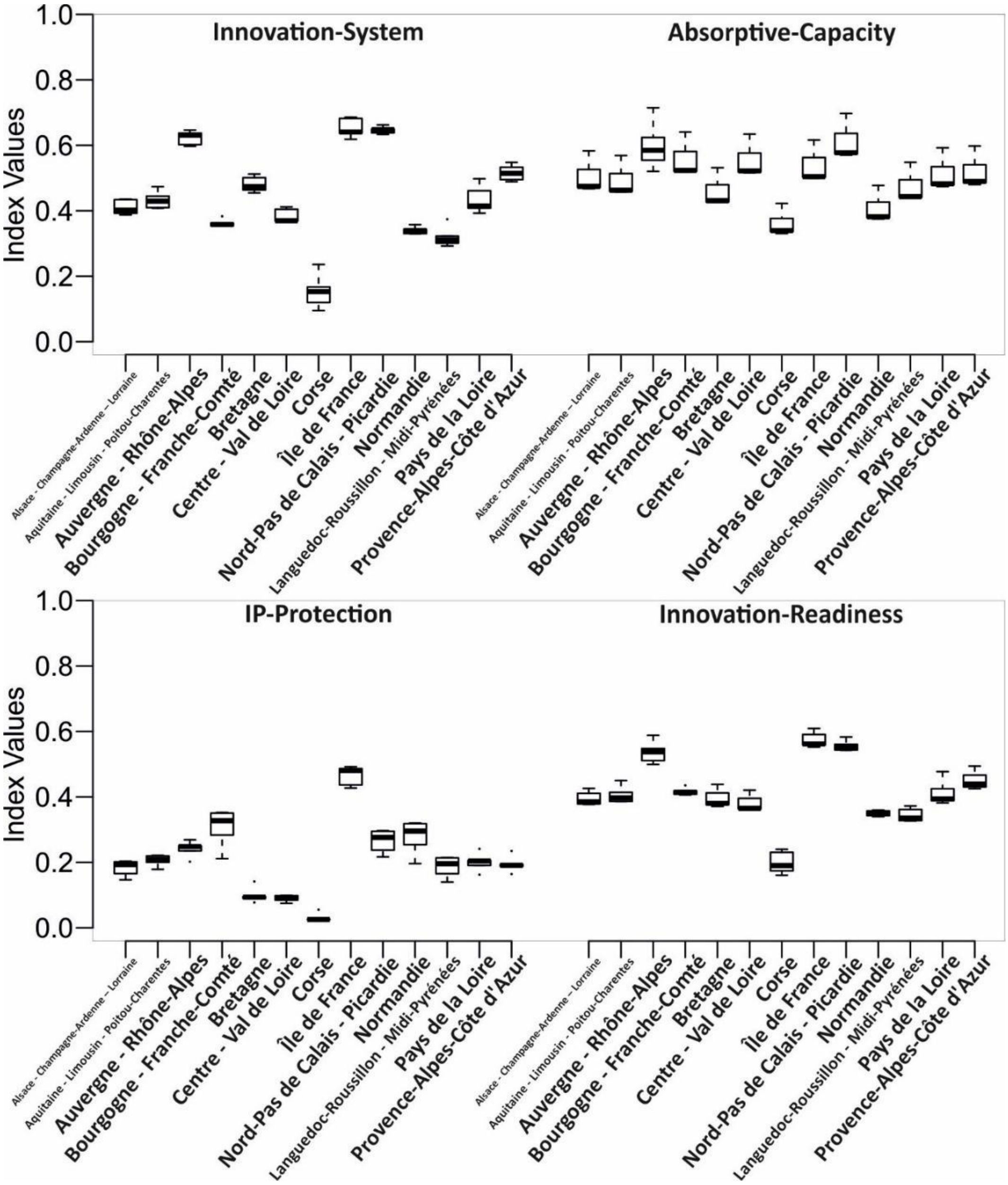


Figure 8. Breakdown of European regions in France (13 regions)



In France (Figure 8), like in the UK, there is considerable variation in the innovation system component. Bourgogne-Franche-Comte, Ile de France (Paris), and Nord Pas de Calais are the best-performing French regions. As with the UK, absorptive capacity is more evenly distributed, with Bourgogne-Franche-Comte and Nord Pas de Calais outperforming Ile de France (Paris). Although IP protection is also relatively evenly distributed, the Ile de France (Paris) is a notable outlier. It has very strong relative performance in this component. Moreover, in the overall innovation readiness index, it is the best-performing region in France, followed closely by Bourgogne-Franche-Comte and Nord Pas de Calais. Like South West England, these regions display consistently strong performance across all three components. Like in the UK, one region (Corse, an island region) performs consistently worse than the others across all components and, consequently, in the overall innovation readiness index. As suggested by the case of Northern Ireland, geography may play a role, hampering the development of these components of innovation.

5. Discussion

The results suggest that large and small countries are likely to behave differently in terms of the consistency of component scores across their regions. These differences relate specifically to which components are consistent and which are disparate. The region that is home to the capital is likely to perform most strongly, primarily because of the IP protection component. More broadly, the results suggest that the relationships between components (e.g., whether they are complementary or substituting) may also differ depending on geographical factors. Also, the relationships may differ for strongly versus weakly performing regions. Comparing cases that are below the 25th percentile in terms of overall innovation readiness with those that are above the 75th percentile reveals very different relationships between the components, as highlighted in Table 5.

Table 5~~:~~. Comparison of cases below the 25th and above the 75th percentile regarding relationships between innovation components

Below 25th percentile in terms of overall innovation readiness (below 0.240)	**Above 75th percentile in terms of overall innovation readiness (above 0.511)**
Below mean final index R(*innovation system, absorptive capacity*) = -0.037 (0.538)	Above mean final index R(*innovation system, absorptive capacity*) = -0.599 (0.000)
Below mean final index R(*innovation system, IP protection*) = -0.026 (0.669)	Above mean final index R(*innovation system, IP protection*) = -0.311 (0.000)
Below mean final index R(*absorptive capacity, IP protection*) = -0.365 (0.000)	Above mean final index R(*absorptive capacity, IP protection*) = 0.172 (0.004)

For the relatively poorly performing cases, there are weak, non-significant relationships between the innovation system and absorptive capacity components and between the innovation system and IP protection components. There is a relatively strong negative significant relationship between the absorptive capacity and IP protection components, indicating a substituting relationship between these two components. In contrast, for the relatively strongly performing cases, all relationships are significant at the 1% level, with a moderately positive (complementary) relationship between the absorptive capacity and IP protection components and strong negative (substituting) relationships between the innovation system and absorptive capacity components and between the innovation system and IP protection components. These results may indicate stronger interconnections between the components in more strongly performing cases and regions. They may also reflect the key role of the broader innovation system in substituting for weaknesses in the other two components (and vice versa). Finally, they may show the complementarity of firm-level absorptive capacity and IP protection in these regions. The substituting relationship between the innovation system component and the other two components also suggests that alternative policy strategies may be possible.

6. Conclusions and future research

In this study, longitudinal analysis of innovation drivers was performed for a large sample of European regions covering 25 countries. The study makes several contributions to the limited literature in this area by providing novel insights (Galbraith *et al*., 2017). First and most importantly, this study gives more detailed insight into innovation adoption across a large sample of European regions and countries. This insight is highly relevant to policymakers seeking to implement effective regional innovation strategies (Nieto and Santamaria, 2010). Second, the study contributes to knowledge on innovation behavior by differentiating between regions within countries and between countries from a regional policy perspective. Innovation practice within high-performing regions (such as London and South West England) can be evaluated to detect similarities and differences and to identify and disseminate best practices. Conversely, underperforming regions (such as Northern Ireland) can be identified and alternative innovation strategies can be implemented.

In terms of the adopted theoretical framework, the study extends the work of Hervás-Oliver et al. (2021a, b) and Beynon et al. (2021). First, it increases the number of relevant variables included in the analysis. Second, it groups these variables into the three innovation components of innovation system, absorptive capacity, and IP protection using regional innovation systems, place-based innovation, and SME innovation. Third, it identifies the relative importance of each of these components depending on the region or country.

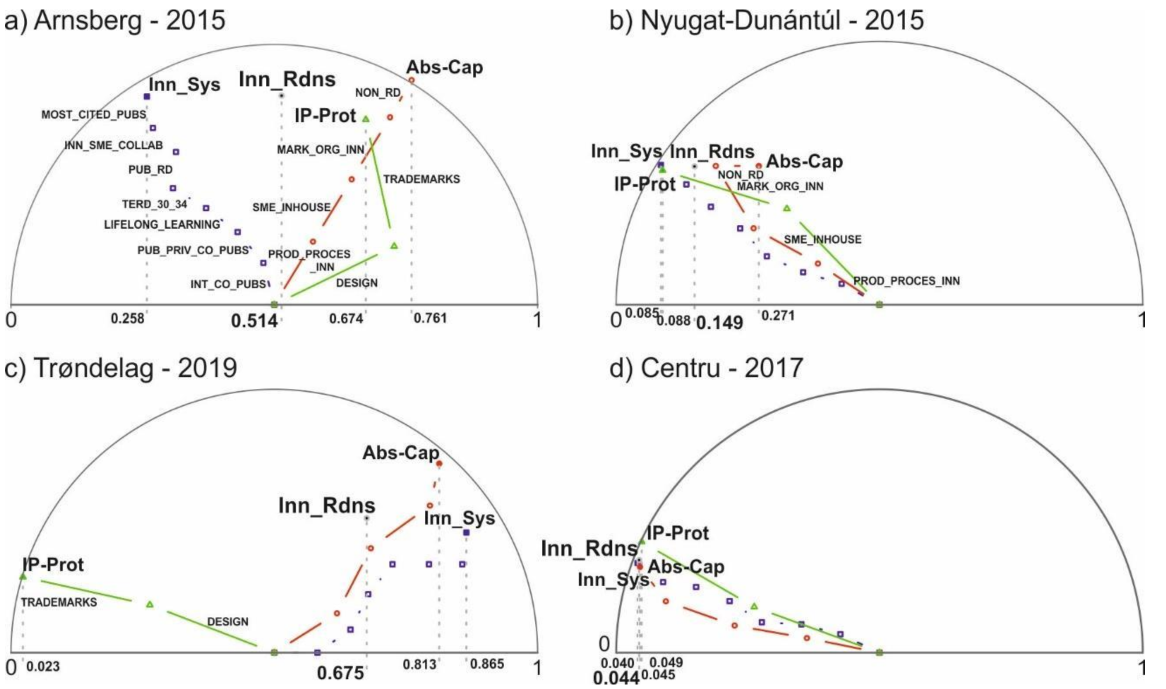
The specific research questions addressed by the study were as follows: What are the sets of innovation-related drivers in Europe? How important is each one? How do they differ across different regions over time? In answer to these questions, the IP protection component plays a strong role in determining the best-performing region within a country. This region tends to be where the capital is located. However, other more geographically peripheral regions in larger countries (e.g., South West England in the UK and Bourgogne-Franche-Comte in France) can also perform strongly. In smaller countries, this strong performance may be more difficult to achieve. Peripheral regions (e.g., the Southern region of Ireland) may be required to focus, at least initially, on one component (innovation system or absorptive capacity) to achieve strong performance. However, for the most geographically peripheral regions these results seem to indicate a set of challenges that current policy has failed to overcome. Therefore, further research is required. In terms of limitations, this study is based on data for a short period. Further comparative studies are required to compare innovation within and between regions and countries. More detailed studies should seek to explore the degree to which these components relate to overall innovation success or failure for regions in terms of sales, high-innovation employment, and the like. This analysis requires novel analytical methods, such as fsQCA. Such methods are also capable of capturing the varying effects of additional influences. Specifically, the analysis should consider effects generated by distinct economic geographies in regions and countries given the broad diversity that exists across Europe. Such effects could be measured by additional variables such as GDP, wage levels, unemployment, and inactivity, among others.

Appendix A

This appendix gives examples of the intermediate constellation graph index approach analysis in this study. The approach was based on the work of Beynon et al. (2016a) and Fuller et al. (2019). This appendix supplements the basic details given in the main text. This content should help readers understand the contribution of constituent variables to the principal components and the subsequent aggregation of evidence on components to form the overall innovation readiness index. The initial analysis was at the component level. Example constellation graphs are shown for four European regions for specific years. Details are given in Figure A1, although not all item labels are shown in all plots.

The results in Figure A1a for Arnsberg (Germany) in 2015 are described to elucidate the process of the constellation graph index approach. In the constellation graph, three sets of line points (i.e., points joined by lines) originate from the center of the baseline. Each line point describes the contribution of the constituent variables of the respective principal component (see Table 3). The length of a line represents the relative size of the loading weights for the set of constituent variables (also shown in Table 3). For the absorptive capacity component shown in Figure A1a, the data in Table 3 indicate that it is has four constituent variables (PROD_PROCES_INN, SME_INHOUSE, MARK_ORG_INN, and NON_RD), with loading weights 0.877, 0.877, 0.869, and 0.510. When these weights are transformed to sum to 1, they become 0.280, 0.280, 0.277, and 0.163. Notably, the constituent line labelled NON_RD is shorter than the others. The line arc direction is based on the f(x) value for the European region, which has domain 0 to 1. It is positioned at an angle of 0º to 180º (from left to right across constellation graph domain) from its relative starting point (center of the baseline of PROD_PROCES_INN then from successive end points of lines).

Figure A1. Example constellation graph results for four European regions



~~The results in Figure A1a for Arnsberg (Germany) in 2015 are described to elucidate the process of the constellation graph index approach. In the constellation graph, three sets of line points (i.e., points joined by lines) originate from the center of the baseline. Each line point describes the contribution of the constituent variables of the respective principal component (see Table 3). The length of a line represents the relative size of the loading weights for the set of constituent variables (also shown in Table 3). For the absorptive capacity component shown in Figure A1a, the data in Table 3 indicate that it is has four constituent variables (PROD_PROCES_INN, SME_INHOUSE, MARK_ORG_INN, and NON_RD), with loading weights 0.877, 0.877, 0.869, and 0.510. When these weights are transformed to sum to 1, they become 0.280, 0.280, 0.277, and 0.163. Notably, the constituent line labelled NON_RD is shorter than the others. The line arc direction is based on the f(x) value for the European region, which has domain 0 to 1. It is positioned at an angle of 0º to 180º (from left to right across~~

~~constellation graph domain) from its relative starting point (center of the baseline of PROD_PROCES_INN then from successive end points of lines).~~

The end point of a full line point denotes the component constellation coordinate for the principal component with the corresponding label. The respective component index value is mapped down from each component constellation coordinate to the baseline of the constellation graph. For Arnsberg in 2015, this value is 0.258 for the innovation system component, 0.761 for the absorptive capacity component, and 0.674 for the IP protection component. The final point shown in the constellation graph, labelled Inn-Rdns (innovation readiness), is the overall aggregated constellation coordinate based on the three principal component constellation coordinates. Their contribution is weighted by the percentage of variance associated with each component. Here, these percentages are 32.381, 24.169, and 14.479 (Table 3). When transformed to sum to 1, they become 0.456, 0.340, and 0.204. The corresponding overall index value is mapped down from this point. For Arnsberg in 2015, this value is 0.514.

Following these details of the constellation graph index approach, further elucidation can be provided through comparisons of the graphs in Figure A1. Noticeable comparisons (for illustrative purposes) include the following:

i) In Figure A1a for Arnsberg (Germany) in 2015, for the absorptive capacity component, the near straightness of the line points ending with a principal component constellation coordinate near the circle edge of the graph signifies near consistent evidence from each constituent variable. Consistency in terms of the normalized constituent variables for this region means that they are nearly the same in value (over the 0 to 1 domain).

ii) In Figure A1b for Nyugat-Dunántúl (Hungary) in 2015, in contrast to the case described in i), for the absorptive capacity component, the line points appear in a zigzag. This situation gives inconsistent evidence from the constituent variables. Hence, the principal component constellation coordinate is far away from the outer circle edge of the graph.

Points i) and ii) relate to the consistency of evidence from the PCA. See Beynon *et al*. (2016a) for a further discussion of how the constellation graph index approach helps show this idea. Comparing results across European regions (for illustrative purposes), the following findings can be highlighted:

iii) In Figure A1c for Trøndelag (Norway) in 2019, the three principal component constellation coordinates, and the subsequent index values, are spread across the constellation graph domain. Notably, IP protection is far away from innovation system and absorptive capacity. This layout indicates substantial variation in the different innovation drivers for that European region.

iv) In Figure A1d for Centru (Romania) in 2017, in contrast to iii), the three principal component constellation coordinates are near each other. Just as evidence from the constituent variables reveals line plots, this layout provides consistent evidence from these principal components.

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